A Categorical Model for Airport Capacity Estimation Using Hierarchical Clustering

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Abstract

Motivated by the need for very inexpensive, easily updated, first-order-accurate estimates of airport capacity required in system-wide analyses, we propose a novel approach to generate a predictive categorical model. The underlying hypothesis tested in this work is that for the same weather conditions airports with a similar runway configuration and fleet mix will have similar capacities. Accordingly, if airport categories with known capacity are defined a-priori on the basis of similarity in fleet mix and runway configuration, then a membership function to the set of categories essentially constitutes a predictive model. We test this hypothesis by formulating and implementing such a model in order to examine its feasibility and discuss key practical considerations. Verification demonstrates model fit error within 4% with a categorical

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training set of 35 major United States airports. Validation against European airports for model representation error is limited by data availability but shown to be in the order of 7-10%. Results suggest that elemental runway configurations are the primary driver for categorical definition, and variations within each category can be associated to fleet mix variations. The implementation of the proposed method to generate other such models with different data sets is encouraged.

Keywords: Airport, Airport Categorization, Capacity, Air Traffic, Clustering, Similarity

1 Introduction

Estimating airport capacity is crucial for planning efforts, and is a key input for a myriad of system performance analyses such as delay and local environmental impacts. Various tools have been developed to this end, ranging from simple analytical functions to very detailed agent-based simulations, thus revealing the different needs and constraints relevant to the characterization of airport capacity. The fundamental tradeoff between fidelity and cost, pervasive in all forms of quantitative estimation, is certainly evident in airport capacity and must be given due consideration when selecting the appropriate tool.

This work is primarily motivated by system-wide capacity, delay, and ensuing environmental impact estimates. Such a capability requires airport capacity estimates subject to distinct requirements: estimates must be generated for a large number of airports, quickly, with modest data and computational burden. In addition, estimate updates reflecting changes at individual airports should be readily implemented and based on deductive first principles. First-order resolution is typical for lower-level components in a system-wide model, and thus is accepted as sufficient for this work.

We propose a methodology to generate airport estimates, consistent with the above requirements, predicated on a categorization scheme as the key enabler for rapid airport capacity evaluations as a function of fundamental airport and operational attributes. Categorization schemes are common in airport analysis, and many have been proposed for various uses including passenger throughput. Categorization holds significant promise as a mechanism for very quick capacity evaluation with first-order resolution. However existing categorization schemes present important shortcomings that lend them unsuitable for the purpose described above. For instance, they do not express capacity in terms of aircraft movements, are subjectively derived, or only apply to very simple runway configurations, to name just a few.

In this paper we examine classification via hierarchical clustering methods as a primary means of generating very inexpensive yet sufficiently accurate capacity estimates for broad sets of airports expected in system-wide studies. The underlying hypothesis is that similar airports naturally exhibit similar capacity characteristics. Accordingly, if a set of airport classes is generated a-priori based on the similarity of its members' capacity and features, one can evaluate the capacity of additional airports by determining the class they most closely resemble.

The work here presented explicitly tests the hypothesis by examining the way in which capacity-related airport attributes may be used to yield a feasible classification scheme via clustering. The feasibility of such an approach for capacity modeling is also addressed in terms of measured accuracy and practical considerations. We first describe the state of the art in Section 2 by providing a review of airport capacity models as well as airport categorization schemes. We then describe the proposed categorical capacity model in Section 3 in terms of the selection of similarity parameters, the set of baseline airports, and their categorization. We also discuss results by examining categorization based on fleet mix and runway configuration. Different candidate categorical schemes are implemented, verified against empirical capacity data, and validated with additional airports. Lastly, we offer conclusions outlining the benefits, limitations, and feasibility of the proposed method airport in producing capacity estimates for system-wide assessment tools.

2 Background

Throughout this paper, in accordance to the Federal Aviation Administration's (FAA), we define capacity as "the maximum sustainable runway throughput, on a long-term basis, of arrivals and departures given a continuous sustained demand".[25] The actual capacity might be different due to variations in fleet mix, weather, control procedures, etc. since all these factors are known to affect required aircraft separation. But as explained in FAA Airfield Capacity Model (ACM), this theoretical capacity is nonetheless valid for comparisons between airports or between developmental alternatives.[25] Similarly, we adopt the ACM definitions for "runway configuration" to refer to a unique way of operating a set of runways for arrivals, departures, or mixed operations, and "runway layout" to refer to the geometric configuration of runways at an airport with no specificity of how they are operated at any given time.

Continuous aircraft movements from airspace to ground and from ground to airspace (i.e., landings and take-offs) can create a heavy traffic. During peak demand hours, runway systems operate near or at full capacity and become the bottlenecks of the airspace system.[23] Overall runway capacity is one of the most important factors governing airport throughput.[23] Consequently, most of the existing capacity estimation techniques and computer models focus on runway capacity, an often ignore the more detailed infrastructure and surface traffic flow (taxiway systems, gates, etc.). This representation also lowers the modeling sophistication and time cost for high level analysis.

There is a variety of quantitative and qualitative airport categorization techniques reflecting an underlying spectrum where detail and modeling sophistication trade off with implementation and execution cost (person hours, data, and computer resources).

2.1 Survey of Capacity Estimate Models

Perhaps one of the most widely referenced sources on airport capacity estimation is the FAA Advisory Circular on Airport Capacity and Delay (AC: 150/5060-5) where guidance on the computation of airport capacity is provided along with a listing of related computer programs.[7] Airport planners still use it as the primary guidance when it comes to capacity calculation, even though it was first published in 1983 and last updated 20 years ago.[2] The computer programs described in AC:15/5060-5 are Simulation Model (SIMMOD), Airport Model, Airfield Delay Simulation Model (ADSIM) and Airfield Capacity Model (ACM). More recently, the Airport Cooperative Research Program (ACRP) Report 79 grouped these and other widely used capacity estimate models under five levels according to their fidelity and sophistication.[2] Table 1 summarizes these five model capability levels and provides modeling examples, application areas, limitations and required data inputs at each level.

Table lookups such as those in FAA AC: 150/5060-5 [7] Chapter 2 are generally high level approaches and are not flexible in terms of different airport layouts and operations. This particular example tabulates capacity values under visual flight rules (VFR) and instrument flight rules (IFR) capacity as a function of runway configuration and aircraft class. It is limited to 19 different runway configurations with 5 different intervals of percent aircraft class. More importantly, all underlying assumptions are fixed. Charts and graphs, such as those in FAA AC: 150/5060-5 [7] Chapter 3, are very similar to table lookups albeit with a graphical representation. Charts and graphs are commonly used whenever the capacity estimate involves multiple value lookup steps. For instance the charts in FAA AC: 150/5060-5 are used to estimate capacity for runway, taxiway, and gate group components, ultimately aggregated to airport capacity. This approach gives more freedom to the airport planner in terms of choosing the overall configuration that best represents the airport of interest compared to the table lookup approach. The planner can also analyze each component's capacity separately. However, this method is also limited by the configurations given in the charts/graphs and their underlying assumptions.

The ACM [25] is an analytical model that calculates the maximum throughput of a runway for user-specified runway configurations, aircraft mix and three separate weather conditions. Effects of taxiway and gate components on capacity are not explicitly incorporated. The ACM user can implement different air traffic control (ATC) strategies such as changing minimum separation between successive arrivals. The ACM only models a handful of basic runway configurations directly, but is able to provide estimates for more complex configurations as combinations of simpler ones. This model has been used by FAA for the Airport Capacity and Delay Force studies.

The Airfield Capacity Spreadsheet Model is a direct outcome of ACRP project 79 [2], and is implemented as a set of Excel spreadsheets with the purpose of automating manual lookup operations with tables and graphs (i.e., Levels 1 and 2) and more flexible analytical models (Level 3) to simulate case-specific conditions (i.e., Level 3). The methodology behind it is primarily based on ACM but also incorporates minor improvements resulting is some added flexible against underlying assumptions of tables and charts.

Recently the FAA announced that it had replaced the ACM with *runway*Simulator [5],[22], one of its main runway capacity estimation tools, and made it publicly available. This medium resolution model simulates a scenario-based traffic at an airport described by runway configuration, fleet mix and separation rules. The maximum sustainable throughput capacity is obtained by simulating continuous runway operations for several hundred hours. The model assumes that downstream resources such as taxiways, gates, etc. have a greater or equal capacity than the runways.

The highest level of model resolution and sophistication is observed in direct numerical simulations of the airport surface and immediate airspace. ACRP

Report 79 [2] identifies this type of tool as Level 5 (see Table 1). SIMMOD [6] and Total Airspace and Airport Modeler (TAAM) [17] are the most widely used models in this level. These are sophisticated simulation models that are used to make detailed analysis on various air traffic scenarios. SIMMOD uses discrete event simulation whereas TAAM uses 3D models, but they both model individual aircraft movements on ground (through runways, taxiways and gates) as well as in airspace. The most significant drawback of these simulators is that the inherent requirements for extensive input data, as well as time and effort for set up and calibration typically in the order of months.

Overall, the spectrum of airport capacity modeling tools may be most directly characterized in terms of the tradeoff between scope and accuracy vs. setup and evaluation cost. Highly detailed models can yield more accurate results, but they also depend on the accuracy of overwhelming amount of inputs. Lower fidelity models comes with lower cost, require less training, and time to set up and run these models are minimal. However, they are restricted by their underlying assumptions and typically limited to a set of runway of configurations, and therefore less suitable for complex airport layouts and detailed analysis. Furthermore, some of the capacity models are publicly available, some are proprietary and some must be purchased at a cost.

2.2 Existing Airport Categorization Techniques

The literature contains a variety of airport categorization schemes with respect to several criteria depending on the purpose of the application. There is no formal standard for airport capacity classification, although by far the most common technique is grouping based on annual passenger traffic rather than of aircraft movements.

As shown in Table 2 FAA uses annual passenger boarding to classify airports in order to determine eligibility for the federal government's Airport Improvement Program funding.[9],[10] The use of this categorical scheme outside the United States should therefore be considered carefully. Similarly, Airports Council International (ACI) Europe classifies European airports in 4 different groups based on number of passengers.[3]

Ottl and Bock categorize airports for air traffic simulation purposes by defining case-specific similarity parameters, but does not cover airport infrastructure.[13]

Bock et al. propose a clustering methodology that is based on runway infrastructure and air traffic.[21] However this methodology consists of only elemental runway layouts and does not take runway-specific operations into account. Hence, it cannot be applied to airports which have complex runway configurations. Moreover, the considered air traffic cases are specific to the targeted air transport market.

Bernardo proposes a set of generic airports for rapid fleet level noise prediction by combining generic runways and generic infrastructures. But the creation of these generic infrastructures is based on somewhat qualitative observations although they are supported by statistical analysis supporting some of these groupings. Overall the approach is not immediately suitable for capacity purposes.[14]

In summary there is no categorization technique in literature that is specific to capacity assessments, purely quantitative, and is broadly applicable to all airports no matter how complex their infrastructures are. The method proposed here aims, in part, to fill this gap.

3 Development of the Categorical Capacity Model

Our approach to develop the categorical capacity model is as follows: first, we define and select similarity parameters to measure similarity between airports. Second, we choose a baseline set of airports that sufficiently spans the range of variability of similarity parameters, and for which requisite data is readily available. Third, the baseline set is subject to a grouping process using similarity parameters resulting in the characterization of representative airport for each category. Each of these representative airports is generic, meaning they are an abstraction of the constituent airports of their category. Finally, generic airports are verified for accuracy against the baseline airports and validated against a separate and independent set of airports for model representation quality.

3.1 Selection of similarity parameters

The similarity between airports can be characterized with certain measurable attributes, referred here as similarity parameters. For this study they should be those known to govern capacity and suitable for quantitative assessments. The choice of these similarity parameters can vary based on the specific purpose of analysis and capacity model assumptions. Some examples are runway infrastructure, operational fleet mix, dominant weather conditions, available equipment or technology, etc.

For this study we adopt two primary characteristics known to be primary contributors to airport capacity: runway configuration and fleet mix. Use of runway configuration as a similarity parameter is consistent with the assumption that airport capacity is governed (constrained) by the runway system and that other systems such as taxiways can be neglected. Fleet mix is also a very important variable which enables system-wide studies with projections into the future since it is typically desired to assess the effect of fleet changes on system wide metrics like delay, fuel burn, and noise. Moreover, it is another essential factor that determines the overall runway capacity due to different spacing rules between various types of aircrafts during arrival and departure operations. FAA's spacing rules are specific to aircraft weight categories for each operation scenario as summarized in Table 3.[10]

Weather conditions are a determinant for aircraft separation [10], and by extension to airport capacity. Runway configuration is also known to be strongly influenced by weather (as well as operational phenomena such as arrival/departure banks.) However, we do not adopt weather as a similarity parameter. Contrary to fleet mix and runway configuration, which can be defined specifically for each airport and can therefore be used as the basis for measuring similarity, aircraft separation as a function of weather is standard (as shown in Table 3 [10]) and universally applied to all airports. Accordingly, the capacity estimate for a given airport indeed changes with weather, and the relative change in capacity due to weather is different for different airports. However, weather has a diminishing differentiating effect on the estimation of capacity for increasingly similar airports on the basis of fleet mix and runway configuration. This is true even if one opts to address weather as a parameter specific to each airport, for instance by determining prevalent weather conditions. The fleet mix is not affected by weather, and the effect on runway configuration choice as a function of weather is by definition directly captured by runway configuration as a differentiating parameter. The above consideration is most readily evident by the fact that all capacity models regardless of their level of sophistications handle weather conditions in the same manner, namely, as a nominal variable. The capacity model for a given airport is set up with an assumed runway configuration and fleet mix, and is instantiated for each weather condition with the corresponding aircraft separation to produce corresponding capacity estimates.

3.2 Selection of baseline airports

The baseline set of airports should be chosen to capture as much variability as possible over similarity parameters so that generic airports resulting from the categorization process provide good representation of the broader superset of airports and consequently good predictive power for airport capacity. In this sense the baseline set of airports should also be those that play a sufficiently significant role in system-wide capacity. At the same time from a practical standpoint the choice of airports for the baseline set is also driven by the availability of airport information in terms of similarity. Accordingly, we select the FAA's OEP 35 (Operational Evolution Partnership) because they account for a significant fraction of commercial operations activity in the U.S. and have been recognized as critical system-wide capacity bottlenecks.[4] This set collectively offers ample variety in terms of fleet mix and runway configurations. Information on all of these airports such as airport layout, prevalent configuration use, and traffic counts for fleet mix estimates, are readily available from FAA resources (including FAA capacity benchmarking studies). As an added benefit information is available for OEP airports for which there have been recent runway additions and runway configuration, allowing for the inclusion of the same airport as two separate samples. For example, Charlotte/Douglas International Airport (CLT) changed the utilization of its runways because a new runway (18R/36L) was opened on January 6, 2010, as depicted in Fig. 4 Two different configurations are included in the baseline set as CLT 1 and CLT 2.

3.3 A-priori capacity estimates for baseline airports

In consideration of the capacity modeling options outlined in Section 2.1 we generate estimates with the ACRP's Airfield Capacity Spreadsheet Model (hereinafter referred to as the ACRP model) given its public availability and adequate balance of fidelity and effort for this study. As explained in Section 2.1 the ACRP model incorporates elements of table/graph look-up models and analytical model features of the ACM on which it is largely based. The mathematical approach to estimate capacity, say for arrivals on a single runway, is to determine the minimum time between successive arrivals and departures for all possible aircraft weight class line-ups and calculate the maximum number of operations per hour. Based on the fleet mix input, the model creates a pairing probability matrix (probability is $p_i p_j$ where subscripts i and j indicates leading and trailing aircrafts, respectively) for arrivals where aircraft weight classes are paired to realize all combinations of landing sequences. Then, required separation time for arrivals (t_{ij})) is determined from scenario-specific ATC rules and approach velocities of subsequent aircrafts (see Ref. [10] for details about separation time and distances). The inter-arrival time t_A is given in Eq. 1 as:

$$t_A = \sum_{ij} p_i t_{ij} p_j \tag{1}$$

Accordingly, the runway landing capacity Λ_A is given by Eq. 2:

$$\Lambda_A = 1/t_A \tag{2}$$

Runway departure capacity is calculated in a similar manner. For mixed operations where a single runway is utilized for both landings and take-offs, either arrival or departure capacity takes priority or departures are randomly distributed between arrivals such that a maximum number of operations is achieved. For more detailed analysis regarding these scenarios, the reader can refer to Ref. [19]. Different runway configurations such as parallel or intersecting runway systems are captured by the ACRP model by making necessary adjustments to the aircraft separation distances or times following the current separation rules for dependent runway usage.

The main drawback of the ACRP model is that it is limited to three types of runway models: single runway, dual parallel runways and two intersecting runways, as shown in Fig. 1. The dual parallel and two intersecting runway models offer eight different scenarios to choose from when the layouts shown in Fig. 1 are compared with arrival, departure and mixed operations. However, it is not possible to model more than two parallel dependent runways or, in general, more complex configurations. To overcome this limitation we adapt the general approach in the ACM and treat the single runway, two parallel runways, and two intersecting runways as "elemental configurations" (see Fig. 2). Complex configurations are those generated from the combination and aggregation of elemental ones. Complex configurations defined in the ACM are shown in Fig. 3. The ACM user's guide [25] provides details on the logic for combining elemental configurations to generate capacity estimates for complex ones. We adopt these combinatorial rule set and apply it on the capacity estimates of elemental configurations produced with the ACRP model in order to generate capacity for complex configurations.

3.4 Categorization of baseline airports and generation of generic airports

The purpose of categorically grouping baseline airports is to create, for each category, a generic airport for which the capacity estimate will be an adequate approximation for all airports in that category by virtue of their similarity. Again, the hypothesis central to this work is that similar airports naturally exhibit similar capacity characteristics. Since there are no predefined groups to which airports can be assigned, and relationships among all the variables are unknown, an unsupervised machine learning approach for developing relational or membership information is required. One such method is clustering, also known as "data clustering [...], cluster analysis, segmentation analysis, taxonomy analysis, or unsupervised classification." [12] Clustering is an indirect data mining approach "to create groups of objects, or clusters, in such a way that objects in one cluster are very similar and objects in different clusters are quite distinct." [12] Clustering is hugely popular across a myriad of data analysis applications, in part due to its relative simplicity and low computational cost for modestly sized problems. Accordingly, there is large body of work on clustering describing numerous methodological variants and modifications geared to improve performance for specific types of problems and data sets.

In this work we utilize agglomerative hierarchical clustering because it is highly efficient and suitable for modestly sized data sets. This approach is preferred over divisive hierarchical clustering which is known to be considerably more complex and computationally intensive (except for a few special cases). In agglomerative clustering all elements are initially treated as their own cluster, and in a recursive manner the two closest (most similar) clusters are combined into a single cluster, until there is only one cluster containing all the elements. The output is a hierarchical clustering tree where there is an optimal solution at each hierarchical level. The selection of a single solution, namely the level in the hierarchical tree, is conducted by the analyst and is typically informed by examining graphical representations of clustering results. A dendrogram visualizes the hierarchical tree, and a scree plot depicts cluster pair joins in the abscissa and the distance bridged to join the clusters in the ordinate. [18] In the scree plot a sudden jump in bridged distance indicates a natural break in hierarchical data clustering, which in practice is typically used as the selected solution in the hierarchical clustering tree (or at least as a solution of interest, with the selected solution being not too distant in the scree plot).

We cluster the set of baseline airports according to the two similarity parameters, fleet mix and runway configuration, while proposing and testing different ways of doing so from logical and practical standpoints.

3.4.1 Clustering based on fleet mix

Fleet mix information for OEP 35 airports was gathered from the FAA's Traffic Flow Management System Counts (TFMSC), which provides information on traffic counts by airport.[11] Traffic counts data from January 1st to December 31st 2013 was grouped by weight class for commercial aircraft operations of OEP 35 airports separately, so that it can be an input to the capacity model. The year 2013 was chosen as the reference year because it was the most recent data available at the time. Moreover, the relative allocation of traffic across weight classes was observed to not change significantly over preceding years.

We apply agglomerative hierarchical clustering on the fleet mix data set of the OEP 35 airports. Fig. 5 shows the resulting clusters with airport identities in a dendrogram and accompanying scree plot below where a jump in the bridged distance is clearly discernible. This level of the hierarchical tree is selected, shown as a solid line on the scree plot and as a vertical dashed line on the dendrogram in Fig. 5, indicating five main clusters for the fleet mix. Initially six clusters had been identified, where the sixth cluster only consisted of one element: Honolulu International Airport (HNL). This result is not surprising since HNL observes a very large share of heavy class aircraft given its geographical isolation in the Pacific requiring long range transports. To test the uniqueness of HNL and the effect it has on the hierarchical clustering we excluded it from the sample and repeated the analysis. The results were practically identical in terms of the hierarchical tree, drop in the scree plot, and member composition of the 5 resulting clusters. This suggests that HNL has no impact on the categorization of the rest of airports and would only be carried forward as the single member of a cluster that, in our opinion, is quite unique and not representative of other airports beyond the OEP 35. We therefore remove HNL from the set and carry forward the 5 fleet mix clusters identified. Parallel coordinate plots for each cluster given in Fig. 6 illustrate how fleet mix of each airport is distributed over the weight classes. Representative fleet mix distributions for these five clusters are obtained by averaging the distributions in each cluster and are given in Table 4.

3.4.2 Clustering based on runway configuration

Airport runway layouts are easily accessible through online databases such as Ref. [1]. However, information about the most prevalent utilization of runways were not taken from one single source, as the Airport Capacity Benchmark Report 2004 (see Ref. [8]) was the only available FAA report on airport capacity and utilization at the time and it was not up to date. Therefore, configurations of each OEP 35 airport in this report were individually updated by various sources, such as technical reports by airports and publications on airport noise contours. It should be noted that FAA published an update to the 2004 report in 2014 (see Ref. [15]). The 2014 report includes airport capacity profiles for the Core 30 airports and estimates capacity by using *runway*Simulator instead of ACM which was used in the 2004 report. Since the chosen baseline and capacity model are OEP 35 airports and the ACRP model (which is highly based on ACM) respectively, and runway configuration data was already updated by recent publications, the 2014 report was not used in this study.

How to cluster the airports based on their runway configurations is not as obvious or intuitive as clustering based on fleet mix. As defined earlier, runway configuration includes both the runway layout (single, parallel, intersecting, etc.) and operations (arrival, departure, mix) assigned to each runway. If every possible configuration were to be listed, then the dataset to cluster would be very sparse and would not result in a significant amount of reduction in total number of runways. Therefore, an approach which will result in a reasonable amount of clusters while preserving accuracy about airport characteristics is necessary.

In the following subsections four different alternatives to cluster runway configurations are proposed and the advantages and limitations are discussed. The first three alternatives investigate the credibility of clustering airports based directly on runway configurations such that they can later be paired with fleet mix clusters via a Venn diagram. This has been the ordinary method used in literature to group airports as discussed in the background section. In the fourth alternative a different clustering approach in which runway configuration and fleet mix information were incorporated indirectly to the clusters is proposed. The methods are compared with each other and the most promising one is carried forward.

3.4.2.1 Runway configuration characterization - Alternative 1

The simplest way to cluster airports would be to look at their runway layouts and make a list of number of dependent and independent runways in terms of elemental configurations. An example implementation to this approach is demonstrated in Table 5 with some of the OEP 35 airports. Even though this approach seems very convenient in terms of grouping runway configurations, an important disadvantage is that it leads to loss of information about which runways are dependent to each other. Take Chicago O'Hare International

Airport (ORD) as an example. It is listed in Table 5 that ORD as having 6 dependent runways with 2 for arrival, 3 for departure, and 1 mixed use. However it is not possible to tell, for instance, whether the two arrival runways are dependent on each other, or one arrival runway is dependent on a departure or mixed runway. This alternative might be useful only for independent runway analysis, but otherwise it does not offer any differentiation between dependent runways.

3.4.2.2 Runway configuration characterization - Alternative 2

Another scheme considered for the characterization and grouping of airports based on runway configuration incorporates interactions between two runways using the ACRP model's categorization for runway orientations. To visualize how this alternative works, a 3D matrix was generated with different runway orientations and operations at each axis. It can be seen from the 4 by 3 by 3 matrix given in Fig. 7 that this approach allows us to see the operational interaction between two runways, as opposed to Alternative 1. The two points placed on the 3D matrix represent a hypothetical airport. The point on the left shows a parallel dependent arrival runway and a parallel dependent mixed operations runway, and the point on the right shows an intersecting departure runway and another intersecting mixed operations runway. However, it cannot be inferred by just looking at this matrix whether this airport has 3 or 4 runways, i.e. whether there are two different mixed operation runways interacting with the other two runways separately, or there is just one mixed operations runway which is both parallel dependent to the arrival runway and intersecting a departure runway at the same time.

To overcome this issue, one could find the maximum number of runways with the same operation type that a single airport has by looking at each airport in the baseline set. Then a bigger size matrix where each operation is separately laid out is created. This approach was applied to the OEP 35 airport set and the matrix in Fig. 8 was obtained. As it can be seen from the elements on this matrix, it turned out that there are at most 4 arrival, 3 departure and 3 mix runways in the set and they do not necessarily belong to the same airport. All the same type operation runways are numbered so that they are all distinguished from each other. Hence, interactions including more than two runways can be easily shown with this model without any confusion on which runway is interacting with which.

The problem with this model is that a special clustering algorithm which can differentiate the same type operations from different type operations must be adapted or developed, otherwise analysis would be deficient. For this reason, this alternative turns out to be cumbersome rather than simple, fast and convenient.

3.4.2.3 Runway configuration characterization - Alternative 3

The third alternative considered aims to cluster baseline airports based on their runway configurations so that generic configurations can be created. Capacity of an airport can then be calculated by pairing the suitable generic configuration with fleet mix cluster. The difference between this approach and Alternative 1 is that instead of using the actual airport configurations, complex configurations were broken down into elemental ones using the ACM guideline. Accordingly only pairwise runway dependencies are considered and all dependent runway pairs can be separately enumerated and therefore distinguished from all others. Table 6 shows some examples from OEP 35 airports. Since some of the configurations do not exist in the baseline set (e.g. Dependent Arrival-Mixed) clustering need only consider the 8 elemental configurations observed in the baseline set. As it can be seen from Fig. 9, the dendrogram has a natural cut that results in 6 clusters. Parallel coordinate plots that correspond to these 6 clusters are given in Fig. 10. Choosing the representative distribution for each cluster is not trivial, because taking the mean might result in non-integer values for number of runways. Regardless of being non-integer numbers the mean values were still taken to scale the capacity. As a second option, mode of each cluster was also taken to form representative distributions. The resulting representative runway configurations of each approach are given in Table 7 and Table 8.

Nonetheless both approaches face a crucial problem: since capacity is a function of the number and type of elemental runway configurations, and there can be significant discrepancy in the number of each elemental configuration between the generic airport and any of its cluster members, the difference between corresponding capacity estimates can also be significant. Even in the case of only one runway difference the resulting capacity estimate yields a very large error. For example, San Diego International Airport has only one runway with mix operations, and it falls into Cluster 2 which is represented by three single runways when mean values are used and two single runways when mode values are used as it can be seen from Table 7 and Table 8, respectively. When the actual capacity is calculated for SAN and compared to that of the generic airport for Cluster 2 the error is 370% if using the mean distribution and 191% if using the mode. There are also a few cases where the error is as low as 0.5%, but the average error for the baseline set is 55% when represented by the mean distribution and 49% when represented by the mode distribution, which is unacceptable.

3.4.2.4 Runway configuration characterization - Alternative 4

We summarize the observations and findings from the three above alternatives for clustering on runway configuration as a set of conditions that can guide or inform a feasible approach for the same:

i. Runway dependence must be captured in the characterization of configuration and therefore in the clustering analysis because it directly affects capacity estimates.

ii. The characterization of configuration and the clustering method must differentiate between runways, between pairs of dependent runways, and between arrival, departure and mix operations.

iii. Generic airports must not have a different number of runways from cluster elements, or must in some other way correct for discrepancies in this regard when producing capacity estimates.

In consideration of the above stated conditions we propose Alternative 4 for runway configuration clustering. This approach clusters on the basis of *capacity values* for all unique pairwise combinations of elemental runway configuration and fleet mix; it does not cluster runway configurations directly, but rather indirectly and in combination with fleet mix. To do so, the capacity of each and every elemental runway configuration is calculated using each of the five representative fleet mix distributions. Since there are 16 combinations of elemental runway configurations and 5 representative fleet mix profiles the cardinality of the combinatorial set is 80 different elemental configuration fleet mix combinations. Capacity values are generated for each of the 80 combinations, and clustering performed on total number of operations and number of arrivals per hour. The choice of these two clustering parameters allows for a characterization of total throughput and arrival-departure split. Five clusters were obtained from this process as shown in Fig. 11. Each point in Fig. 11 represents the capacity of a fleet mix elemental runway configuration pair. The centroids (designated for each cluster with filled markers) represent the number of operations for the corresponding runway configuration clusters. The data can be tabulated so that every combination of fleet mix and elemental runway configuration is mapped to a corresponding cluster with representative total operations and arrival-departure split capacity values, essentially comprising a look-up table. The latter is provided in the Appendix grouped by cluster.

Estimating airport capacity with the above look-up table therefore only necessitates that the fleet mix cluster be identified, and that the airport be characterized in terms one or more elemental runway configurations. For the given fleet mix and constituent elemental runway configurations representative capacity values can be readily identified and aggregated.

An example usage of this look-up table is given in Table 9 for selected OEP airports. Each airport is characterized by a fleet mix and at least one elemental runway configuration, the combinations resulting thereof mapped to one of the five runway capacity clusters. The two columns of the right in Table 9 indicate the aggregate capacity for total and arrival operations produced as aggregates of the corresponding cluster values. The relative error of the proposed method is discussed in the following section.

This proposed approach satisfies the conditions noted at the beginning of this subsection and yields very inexpensive capacity estimates. It explicitly accounts for and distinguishes between unique instances of single runways and dependent runway pairs, operation type (arrival, departure, mixed), and number of runways without resulting in discrepancy-induced error.

Two critical observations pertinent to the hypothesis of this study and the demonstration of a feasible method must be stated at this point. As intended, the resulting clusters are such that the capacity of elements within a cluster are similar, and at the same time sufficiently different from those belonging to another cluster. However, inspection of cluster membership indicates that elemental configuration is a dominant feature over fleet mix, the latter present evenly within each cluster. We also find that in some cases very different elemental configurations with different fleet mixes can have similar capacity (see for instance Cluster 1). In other cases similar capacity is driven mainly by the type of elemental configuration but independent of fleet mix, runway dependence, or type of operation (see Cluster 2). In other cases capacity can indeed be attributed to specific elemental runway configurations (see Clusters 3, 4, and 5).

The findings in the look-up table suggest that although fleet mix information is an important factor in estimating the capacity of an airport, it is redundant when this categorical capacity model is to be used. In fact, one only needs to know about the elemental runway configuration to determine which cluster an airport belongs to. This is because different runway configurations create more variability than different fleet mix distributions, resulting in distinct clusters as shown in Fig. 11. Nonetheless, the slight variations from the centroid in each cluster in Fig. 11 are mostly due to differences in fleet mix. This result may differ depending on the chosen baseline airport set.

3.5 Verification of generic airports

Model verification was conducted to assess the representation capability over the training set (OEP 35). To do so estimates for the number of total and arrival hourly operations were produced using the proposed categorical model and with the ACRP model. In both cases, and in the interest of a more direct comparison, representative fleet mixes were utilized. Comparison of capacity estimates and relative error of the proposed categorical model for the OEP 35 set are shown in Table 10.As it can be seen, the model estimates capacity of most of the airports with less than 5% error.

There are only two airports, Boston Logan International (BOS) and St. Louis International (STL) airports, where the model predicts the number of arrivals with a little more than 10% error. The reason behind these errors can be seen by inspecting the labeled points in Fig. 11. BOS was modeled by two mix-operation runways which are parallel and dependent to each other with a representative fleet mix 3 (see Table 4). This configuration is found to be the outermost point from the centroid of Cluster 3 as shown in Fig. 11 and hence it is not surprising to see such an error in terms of capacity. STL was modeled such that it consists of a single runway with mix operations and an arrival and a departure runway which are parallel and dependent to each other, with a representative fleet mix 3. It can be seen from Fig. 11 that STL consists of two different runway configuration clusters: Cluster 1 (dependent runway pair) and Cluster 5 (for the single runway). Again, from Fig. 11, both of these points are located farther away from the clusters' centroids and hence resulting in an aggregated error of more than 10%.

Overall, results shown in Table 10 indicate that the proposed method has, on average, a model representation error of 4% for hourly total operations and hourly arrivals. Note that by definition model representation error for hourly departures is also contained to 4%. We deem this error adequate for the intended use of the model and motivating purpose of this work.

3.6 Validation of generic airports

Model validation was performed to assess the representation and predictive capability over samples outside the training data set. Due to lack of available data about runway utilization of airports outside the United States, the model was compared against only two major European airports for which data was available: Frankfurt International Airport (FRA) and London Heathrow International Airport (LHR). According to 2012 data given in Ref. [16], LHR has two parallel independent runways with mix operations and its fleet mix roughly consisted of 67.1% Large Jet, 1.7% Large 757 and 31.2% Heavy aircrafts. FRA's runway layout and preferred runway operations are shown in Fig. 12.[20] 2006 fleet mix data from Ref. [20] was used to calculate actual capacity of FRA even though Runway 25R/7L did not exist at that time; more recent fleet mix information could not be found. FRA was modeled as having one single arrival, one single departure and two dependent parallel arrival and departure runways with a fleet mix of 20% Large-TP, 60% Large-Jet and 20% Heavy class aircrafts.

Using the look-up table provided in the Appendix, generic elemental runway configurations for LHR and FRA were identified and aggregated into respective airport capacity estimates. The latter are compared against capacity values produced with the ACRP model using the actual airport fleet mix. Results are shown in Fig. 13 and Fig. 14 for LHR and FRA respectively. LHR has a relatively less complex configuration than FRA and therefore the categorical capacity model estimates the capacity of all operations with an error less than that of FRA and arrivals with no error at all. The model also gives acceptable results for FRA (which has a more complex configuration as shown in Fig. 12 and broken down into elemental runways in Fig. 14) by estimating the capacity of all operations with roughly 7% error and arrival operations within less than 5% error, which is deemed acceptable. These results suggest that capacity estimates for airports outside the training set can be produced with fairly small error for simpler configurations, and with error less than 10% for more complex configurations.

It is evident that there is a notable distinction in fleet mix between the European airports and the baseline OEP airports. LHR and FRA have relatively different fleet mixes as a result of operating more international flights than the US airports; for example, heavy class aircraft have higher share in the distribution than the baseline set. This diversity does not pose a problem when matching the airports with their respective clusters since fleet mix information is not used, but results in an error greater than that of the training set.

4 Conclusion

The main purpose of this study is to develop a time and cost effective method to estimate capacity for a large number of airports. Although there are some airport categorization schemes in literature, only a few of them categorize airports based on aircraft movements. The lack of consideration of complex runway layouts and their utilization in these approaches demonstrated the need to create a new extended categorization scheme which is specific to capacity estimation purposes.

To this end, a categorical capacity model was developed by clustering a baseline airport set based on predefined similarity parameters. These parameters were chosen to be fleet mix and runway configuration. Four different alternatives were proposed and examined to create generic airports. The first three of alternatives were shown to be deficient in different respects, but mainly in terms of not being able to differentiate distinct runways or elemental runway configurations. A fourth alternative is proposed and demonstrated to produce estimates with acceptably low error. The proposed approach is predicated on the indirect use of fleet mix profiles, attained via clustering, and elemental runway configurations, to characterize airports and their capacity. Rather than clustering on these attributes as similarity parameters we cluster on capacity values for arrival and total hourly operations for distinct combinations of elemental runway configurations and fleet mix. The resulting clusters indicate that elemental runway configurations, type of operations, and pairwise runway dependence are much more dominant factors for capacity than fleet mix profile. The hypothesis that similar airports have similar capacity is not fully supported by the results presented, particularly in regards to Cluster 1 where very dissimilar elemental configurations with different fleet mix profiles yield similar capacity. Otherwise, Clusters 2 through 5 seem to support the hypothesis.

In addition, the resulting data can be used as a look-up table to determine capacity figures for a given fleet mix profile and elemental runway configuration. For complex configurations capacity is aggregated as a sum of elemental constituents.

The work presented offers an exhaustive look at airport capacity estimation, categorical models for airports, possible modeling avenues and their shortcomings, and ultimately a new and novel approach to characterize airports so that similarity may be directly measured, studies, and leveraged to facilitate a categorical capacity estimation model. In this sense this work offers a new starting point, rather than a final or conclusive answer, in terms of facilitating very fast capacity estimation for large airport sets. Accordingly we encourage the readers to directly use the lookup table in the manner here described to yield capacity estimates, or alternatively to implement the proposed methodology adapted to their needs by applying different airport data, using different capacity estimate models, examining different clustering schemes, including more similarity parameters, etc.

In conclusion, the presented model expedites capacity estimates of large number of airports while still giving sufficiently accurate results. This feature enables system-wide studies with projections into the future through fleet mix distributions. However it should be noted that the model is not meant to be used for detailed analysis due to the limiting assumptions inherent in the model. The main assumption is that capacity of an airport is estimated from the capacity of its runway systems only. The model also does not take weather fluctuations into account and neglects air space restrictions. Furthermore, it does not capture the fact that some aircraft classes are prohibited from using some runways due to noise regulations. Hence, this model is most suitable for high level analysis.

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Tables

Table 1: Proposed levels of modeling sophistication by ACRP Report 79 [2] (Reproduced)

Level	**Description**	**Examples**	**Sample Applications**	**Attributes/ Limitations**	**Data Req.s**
1	Table lookup	Chapter 2 of the AC, new lookup table	Statewide system plans, airport master plans where airfield capacity is not an issue, and small airport master plans	Runways only, simplified airfields, small airports, default assumptions only	Minimal, requiring only an overview of airport runway configuration and aircraft fleet mix
2	Charts, nomographs, and spreadsheets	Chapter 3 of the AC, new spreadsheet model	Statewide system plans, airport master plans where airfield capacity is not an issue, and small airport master plans	Runways only, moderate size airports, less complex airfields, some flexibility in inputs	Minor, requiring airport runway configuration, aircraft fleet mix, exit locations, and percentage of arrivals
3	Analytical capacity models	Airfield Capacity Model	Specialized airfield capacity studies, airport master planning studies, regional airport system planning	Runways only, moderate airfield complexity, taxiways and airspace considered implicitly, flexible input assumptions	More demanding, including aircraft fleet mix, aircraft final approach speeds, aircraft separations, and air traffic control (ATC) rules
4	Airfield capacity simulation models	*runway* Simulator, Flexible Airport Simulation (FLAPS)	Capacity planning of complex airfields or regional airfield/airspace systems	Runways only, complex airfields and airspace, flexible assumptions	More detailed input data than Level 3 models, including close-in arrival and departure flight track geometries and aircraft fleet mix by runway

5	Aircraft delay simulation models	SIMMOD, ADSIM, TAAM	Detailed planning of complex airfields or regional airfield/airspace systems	Runway, taxiways, aprons, gates, and/or airspace; complex airfields (e.g., runway crossings and airspace fix constraints), flexible input	Greatest level of detail about aircraft flight schedule and airfield and airspace configurations, including taxiing routes and aircraft parking positions

Table 2: Categories of airport activities by FAA [9] (Reproduced)

Airport Classifications		**Hub Type: Percentage of Annual Passenger Boardings**	**Common Name**
Commercial Service: Publicly owned airports that have at least 2,500 passenger boardings each calendar year and receive scheduled passenger service	**Primary:** Have more than 10,000 passenger boardings each year	Large: 1% or more	Large Hub
		Medium: At least 0.25%, but less than 1%	Medium Hub
		Small: At least 0.05%, but less than 0.25%	Small Hub
		Nonhub: More than 10,000, but less than 0.05%	Nonhub Primary
	Nonprimary	Nonhub: At least 2,500 and no more than 10,000	Nonprimary Commercial Service
Nonprimary (except commercial service)		Not applicable	Reliever

Table 3: Aircraft weight classes by FAA and the ACRP model [2][10]

FAA Classification	ACRP Classification	Weight Limits
Small	Small-S (Single Engine) Small-T (Twin Engine)	Less than 5,670 kg Less than 5,760 kg
Medium	Small+	Between 5,760 kg and 18,600 kg
Large Commuter	Large-TP (Turboprop)	Between 18,600 kg and 115,670 kg
Large Jet	Large-Jet	Between 18,600 kg and 115,670 kg
B757	Large-757	Boeing 757 all series
Heavy	Heavy	More than 115,670 kg

Table 4: Fleet mix distribution of each cluster by weight classes based on 2013 data with corresponding OEP 35 airports excluding HNL.

Cluster number*	**Small**	**Medium**	**Large Comm.**	**Large Jet**	**B757**	**Heavy**
1	0.33%	0.74%	28.56%	51.65%	13.75%	4.98%
2	1.34%	1.27%	9.09%	82.22%	5.34%	0.74%
3	14.45%	1.30%	22.98%	57.25%	3.92%	0.11%
4	5.20%	5.08%	47.80%	39.36%	2.26%	0.30%
5	0.82%	0.92%	47.29%	45.58%	4.06%	1.33%

*The given fleet mix clusters are mapped to the baseline airports as Cluster 1: ATL, DTW, JFK, LAX, MIA, SFO; Cluster 2: BWI, FLL, LAS, MCO, MDW, PDX, PHX, SAN, SEA, TPA; Cluster 3: BOS, STL; Cluster 4: CLE, IAD, MEM, PIT; Cluster 5: CLT, CVG, DCA, DEN, DFW, EWR, IAH, LGA, MSP, ORD, PHL, SLC

Table 5: A small portion of the OEP 35 airports given in terms of number of elemental runway configurations for Alternative 1. Runway dependency is based on FAA procedures outlined in Ref. [10]. Abbreviations for runways ares: Indp.: Independent runway, Dp.: Dependent runway (parallel, intersecting or converging). For operation types: A: Arrival, D: Departure, M: Mix.

Airport ID	**Indp. A**	**Indp. D**	**Indp. M**	**Dp. A**	**Dp. D**	**Dp. M**
ATL	2	2	0	0	0	1
BOS	0	0	0	0	1	2
ORD	0	0	0	2	3	1
SAN	0	0	1	0	0	0
STL	0	1	1	1	0	0

Table 6: A small portion of the OEP 35 airports given in terms of number of runway configurations to be clustered for Alternative 3. Complex configurations were broken down to elemental ones resulting in less columns. Abbreviations for runways are as follows: S: single, Dp.: Dependent parallel (two runways), I: Intersecting (two runways). For operation types: A: Arrival, D: Departure, M: Mix.

Airport ID	**S A**	**S D**	**S M**	**Dp. A-D**	**Dp. A-M**	**Dp. M-M**	**I A-D**	**I D-M**
ATL	0	0	1	2	0	0	0	0
BOS	0	0	0	0	0	1	0	0
ORD	2	2	0	1	0	0	0	0
SAN	0	0	1	0	0	0	0	0
STL	0	1	1	0	0	0	0	0

Table 7: Representative runway configurations evaluated by taking the mean of each cluster in Alternative 3. Abbreviations for runways are as follows: S: single, Dp.: Dependent parallel (two runways), I: Intersecting (two runways). For operation types: A: Arrival, D: Departure, M: Mix.

Airport ID	**S A**	**S D**	**S M**	**Dp. A-D**	**Dp. A-M**	**Dp. M-M**	**I A-D**	**I D-M**
1	0.56	0.00	0.33	1.33	0.00	0.00	0.00	0.00
2	0.22	0.11	1.67	0.00	0.00	0.00	0.00	0.00
3	1.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00
4	0.14	0.14	0.29	0.14	0.00	0.00	1.14	0.00
5	0.40	0.00	0.40	0.00	0.00	1.00	0.00	0.00
6	1.83	1.50	0.83	0.33	0.00	0.00	0.00	0.00

Table 8: Representative runway configurations evaluated by taking the mode of each cluster in Alternative 3. Abbreviations for runways are as follows: S: single, Dp.: Dependent parallel (two runways), I: Intersecting (two runways). For operation types: A: Arrival, D: Departure, M: Mix.

Airport ID	**S A**	**S D**	**S M**	**Dp. A-D**	**Dp. A-M**	**Dp. M-M**	**I A-D**	**I D-M**
1	0	0	0	1	0	0	0	0
2	0	0	2	0	0	0	0	0
3	1	0	1	0	0	0	0	1
4	0	0	0	0	0	0	1	0
5	0	0	0	0	0	1	0	0
6	3	2	0	0	0	0	0	0

Table 9: Example assignment of runway capacity clusters (RCC) to some of the OEP 35 airports and resulting capacities in terms of total number of all operations and number of arrivals per hour.

Airport ID	**RCC 1**	**RCC 2**	**RCC 3**	**RCC 4**	**RCC 5**	**Total # of Ops.**	**# of Arrivals**
ATL	2	0	0	0	1	223	123
BOS	0	0	1	0	0	91	79
ORD	1	0	0	2	2	271	120
SAN	0	0	0	0	1	43	40
STL	1	0	0	0	1	132	80

Table 10: Comparison of hourly capacities of the baseline airports given by the categorical model and actual configurations. Instead of actual fleet mix, both calculations used representative fleet mix obtained in Section 3.3.1. for consistency.

	Model results		**Actual Capacity**		**Error**	
Airport	**All ops.**	**Arrivals**	**All ops.**	**Arrivals**	**All ops.**	**Arrivals**
ATL	221	120	212	120	4.25%	0.00%
BOS	107	69	100	62	7.00%	**11.29%**
BWI	132	80	131	84	0.76%	4.76%
CLE	107	69	108	68	0.93%	1.47%
CLT 1	86	80	90	84	4.44%	4.76%
CLT 2	180	80	175	84	2.86%	4.76%
CVG	175	120	183	126	4.37%	4.76%
DCA	150	109	154	114	2.60%	4.39%
DEN	268	160	269	168	0.37%	4.76%
DFW	264	160	254	168	3.94%	4.76%
DTW	175	120	170	120	2.94%	0.00%
EWR	89	40	85	42	4.71%	4.76%
FLL	43	40	46	42	6.52%	4.76%
IAD	177	120	167	117	5.99%	2.56%
IAH	225	120	227	126	0.88%	4.76%
JFK 1	86	80	87	80	1.15%	0.00%
JFK 2	91	40	91	40	0.00%	0.00%
LAS	132	80	128	84	3.13%	4.76%
LAX	178	80	165	80	7.88%	0.00%
LGA	89	40	84	42	5.95%	4.76%
MCO	193	149	204	156	5.39%	4.49%
MDW	89	40	85	42	4.71%	4.76%
MEM	180	80	171	78	5.26%	2.56%
MIA	178	80	164	80	8.54%	0.00%
MSP	129	120	132	126	2.27%	4.76%
ORD 1	225	120	224	126	0.45%	4.76%
ORD 2	271	120	267	126	1.50%	4.76%
PDX	86	80	92	84	6.52%	4.76%
PHL	89	40	85	42	4.71%	4.76%
PHX	132	80	128	84	3.13%	4.76%
PIT	132	80	125	78	5.60%	2.56%
SAN	43	40	46	42	6.52%	4.76%
SEA	150	109	154	114	2.60%	4.39%
SFO	178	80	162	80	9.88%	0.00%
SLC	129	120	135	126	4.44%	4.76%
STL	132	80	124	70	6.45%	**14.29%**
TPA	86	80	92	84	6.52%	4.76%
				Average Error:	***4.19%***	***4.00%***

5 Figure Captions

Fig. 1: ACRP Model's dual parallel and intersecting runway layouts. [2] The layouts shown here are listed as: (a) Dependent parallel (b) Independent parallel (c) Close, diverging (d) Open end (e) Far, converging (f) Closed end

Fig. 2: Elemental runway layouts (a) Single runway (b) Parallel runways (can be dependent or independent based on runway separation between the two centerlines) (c) Intersecting runways

Fig. 3: Some complex runway layouts included in ACM [25]

Fig. 4: Two layouts of Charlotte/Douglas International Airport. (a) CLT 1: Runway layout and utilization before January 6, 2010 (before Runway 18R/36L was opened).[8] (b) CLT 2: Runway layout and utilization after January 6, 2010.[24] Schematics are for demonstration purposes only and not to scale.

Fig. 5: Fleet mix clusters dendrogram after excluding HNL from the OEP 35 list.

Fig. 6: Parallel coordinate plots for each fleet mix cluster after excluding HNL from the OEP 35 list.

Fig. 7: Alternative 2 representation of possible runway configurations. Points on the cube represent two examples to different operational interaction between two runways.

Fig. 8: Alternative 2 representation of possible runway configurations where each runway operation is numbered to distinguish dependent configurations.

Fig. 9: Runway configuration clusters dendrogram for Alternative 3.

Fig. 10: Parallel coordinate plots for each runway configuration cluster.

Fig. 11: Five clusters obtained from Alternative 4 given with circled cluster numbers.Each point in the figure represents a fleet mix-runway configuration pair. Centroids of each cluster are shown with filled markers. The gray areas are to highlight different clusters and for demonstration purposes only. Detailed configurations were given with corresponding fleet mix clusters for exemplification.

Fig. 12: Layout of Frankfurt International Airport with preferred arrival and departure directions according to Ref. [20]. Schematic is for demonstration purposes only and not to scale.

Fig. 13: Capacity of generic airport vs. actual airport comparison for London Heathrow Airport.

Fig. 14: Capacity of generic airport vs. actual airport comparison for Frankfurt Airport.

Figures

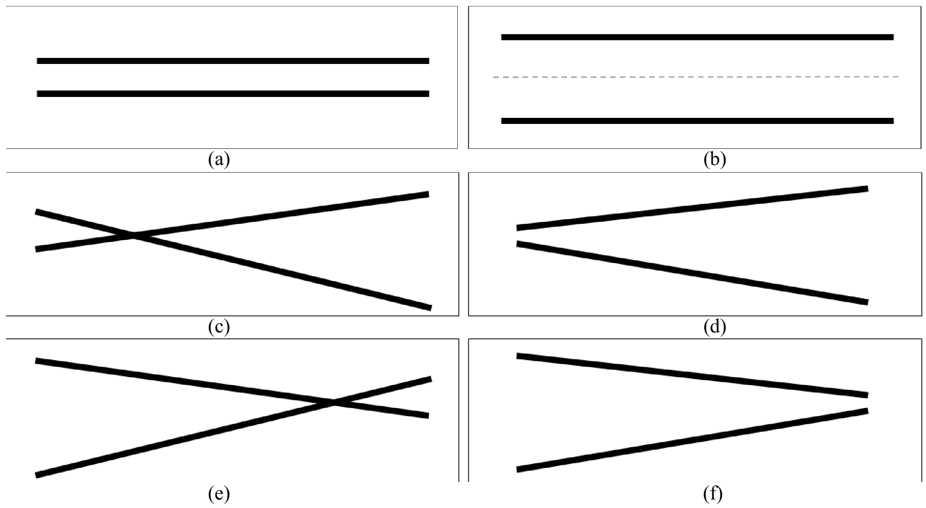


Fig. 1

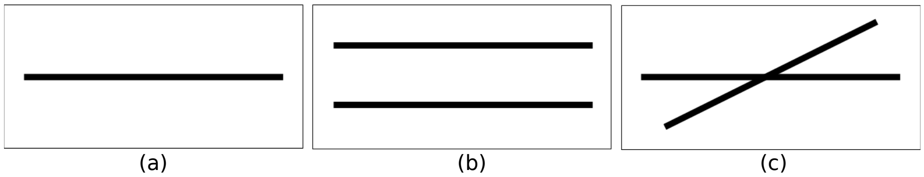
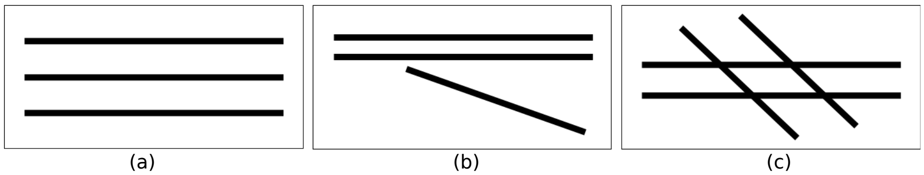


Fig. 2



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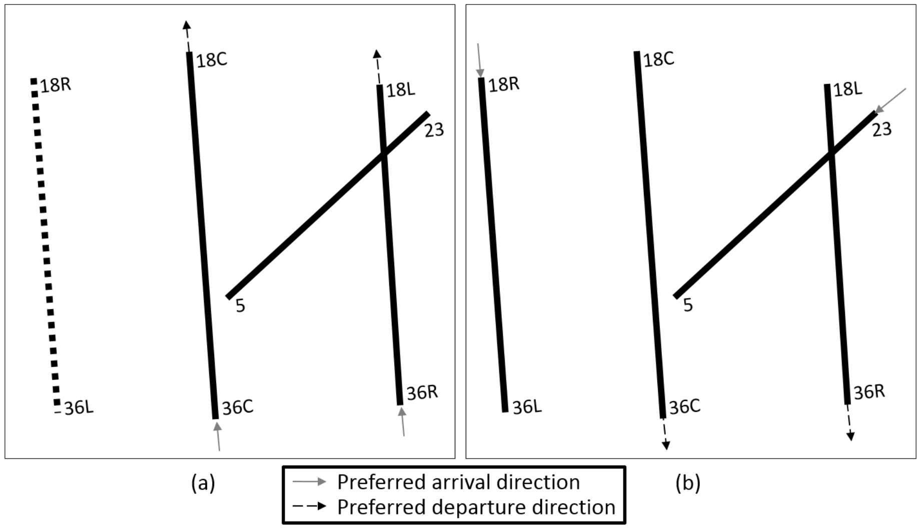
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(a)
(b)
Preferred arrival direction
Preferred departure direction

Fig. 4

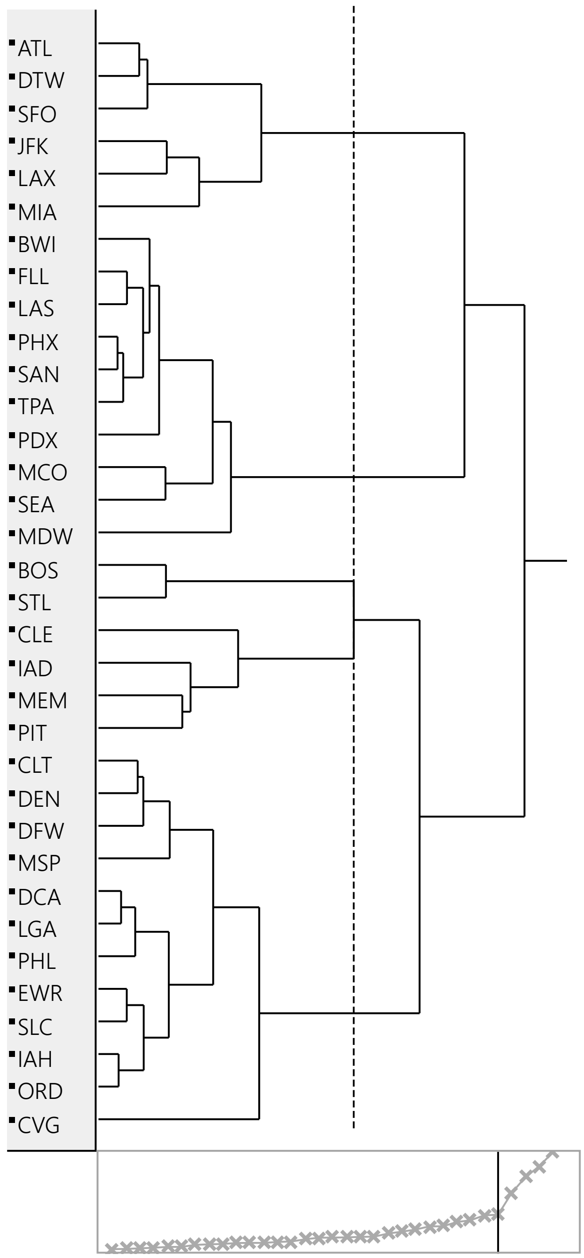
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Fig. 5

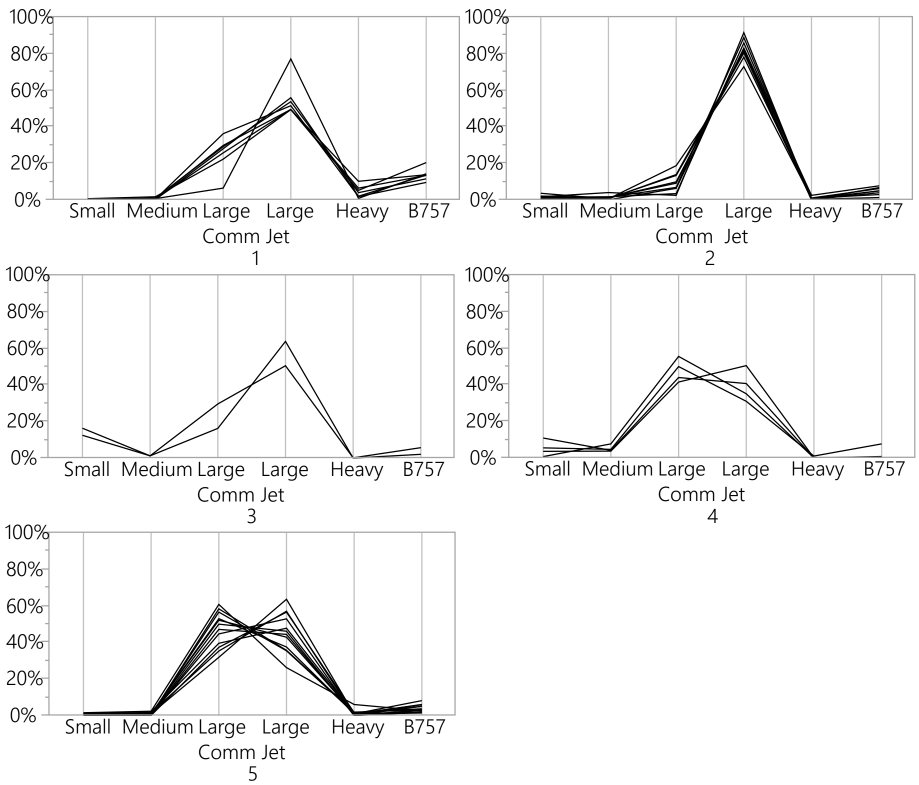
100%
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Fig. 6

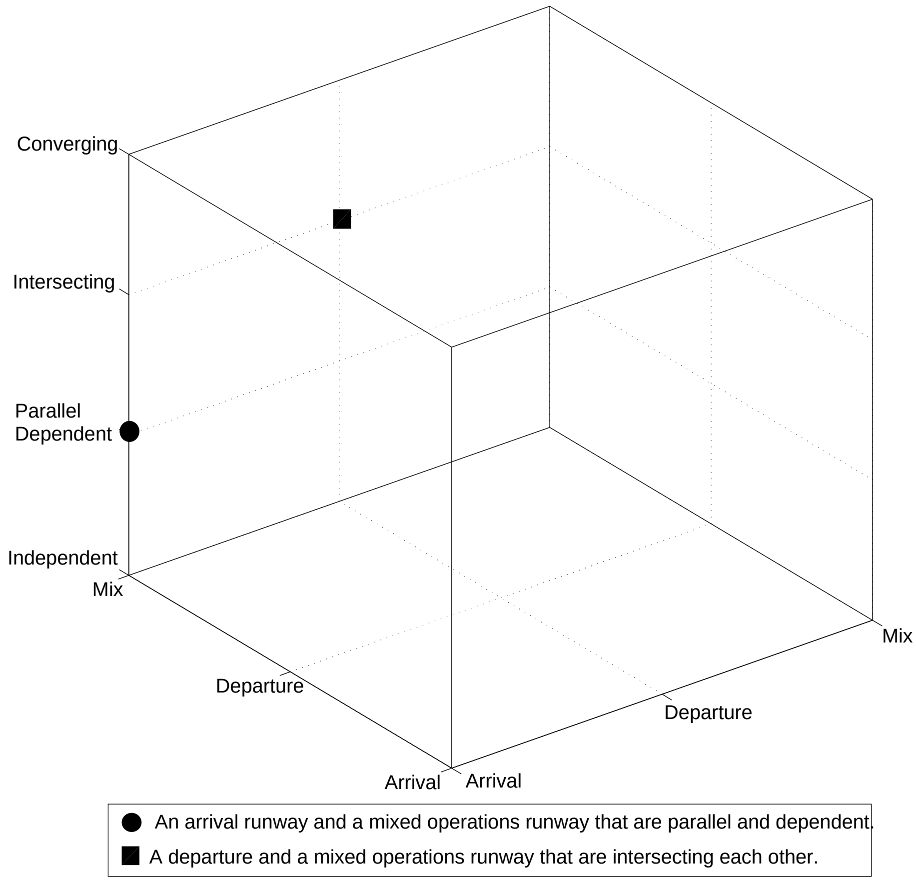
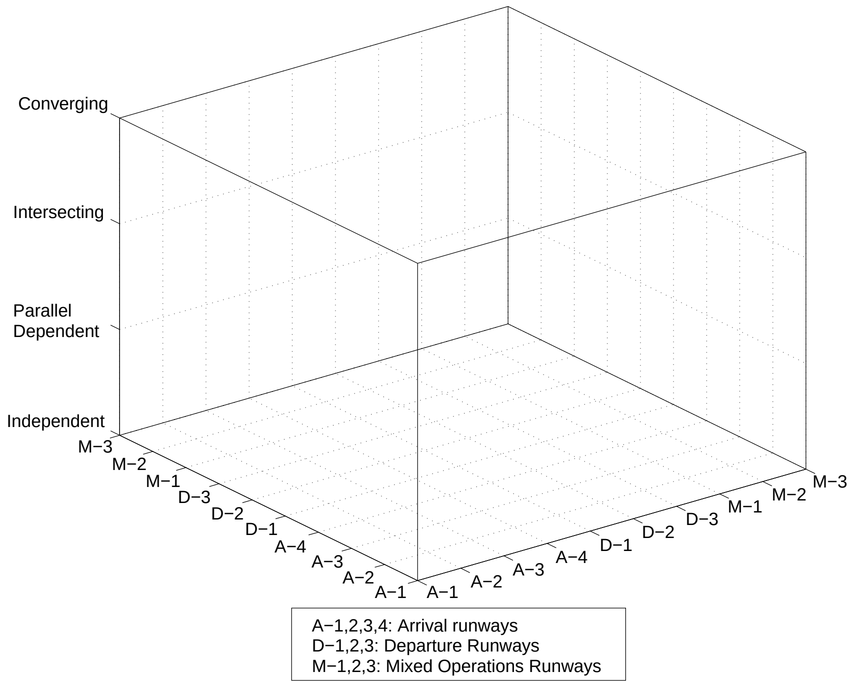

Converging
Intersecting
Parallel
Dependent
Independent
Mix
Departure
Arrival
Arrival
Departure
Mix
An arrival runway and a mixed operations runway that are parallel and dependent.
A departure and a mixed operations runway that are intersecting each other.

Fig. 7



Converging
Intersecting
Parallel
Dependent
Independent
M−3
M−2
M−1
D−3
D−2
D−1
A−4
A−3
A−2
A−1
A−1
A−2
A−3
A−4
D−1
D−2
D−3
M−1
M−2
M−3
A−1,2,3,4: Arrival runways
D−1,2,3: Departure Runways
M−1,2,3: Mixed Operations Runways

Fig. 8

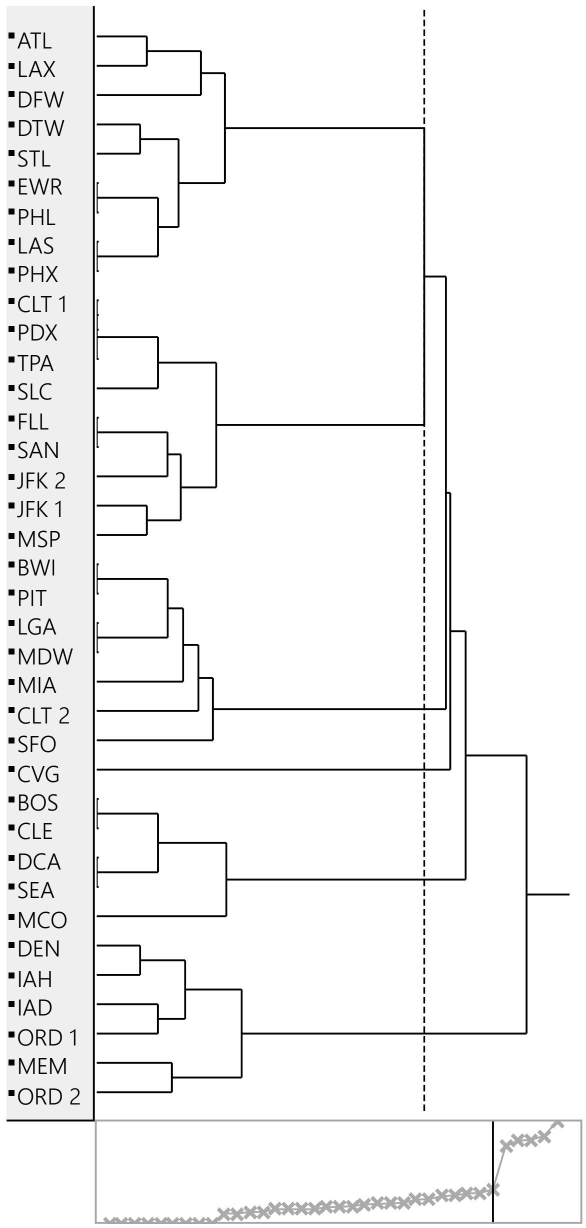

ATL
LAX
DFW
DTW
STL
EWR
PHL
LAS
PHX
CLT 1
PDX
TPA
SLC
FLL
SAN
JFK 2
JFK 1
MSP
BWI
PIT
LGA
MDW
MIA
CLT 2
SFO
CVG
BOS
CLE
DCA
SEA
MCO
DEN
IAH
IAD
ORD 1
MEM
ORD 2

Fig. 9

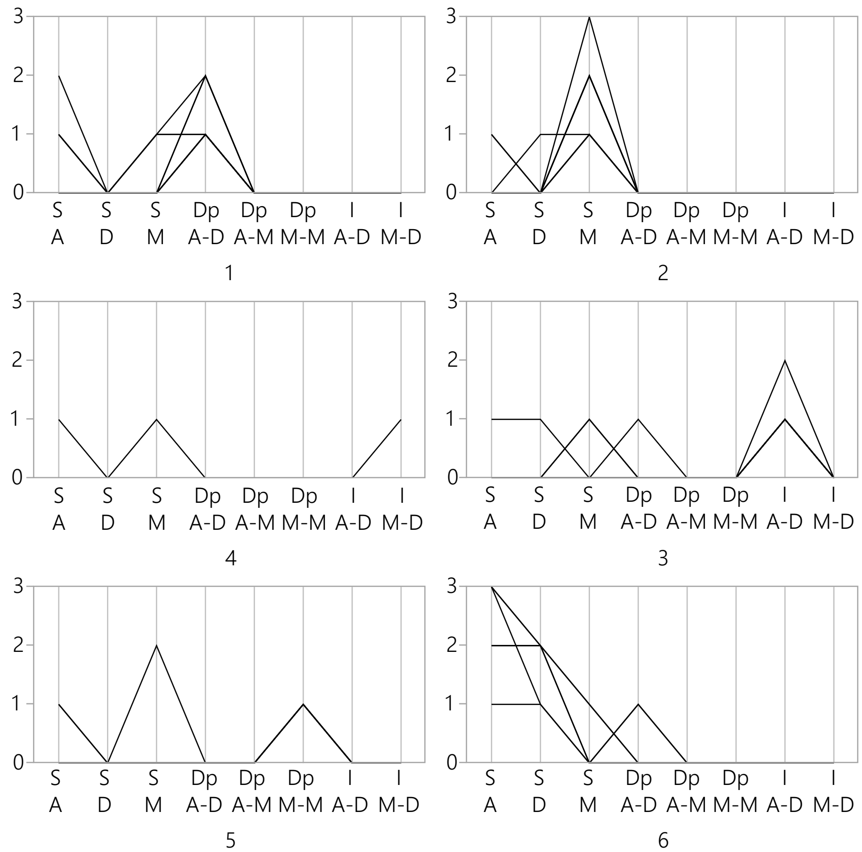
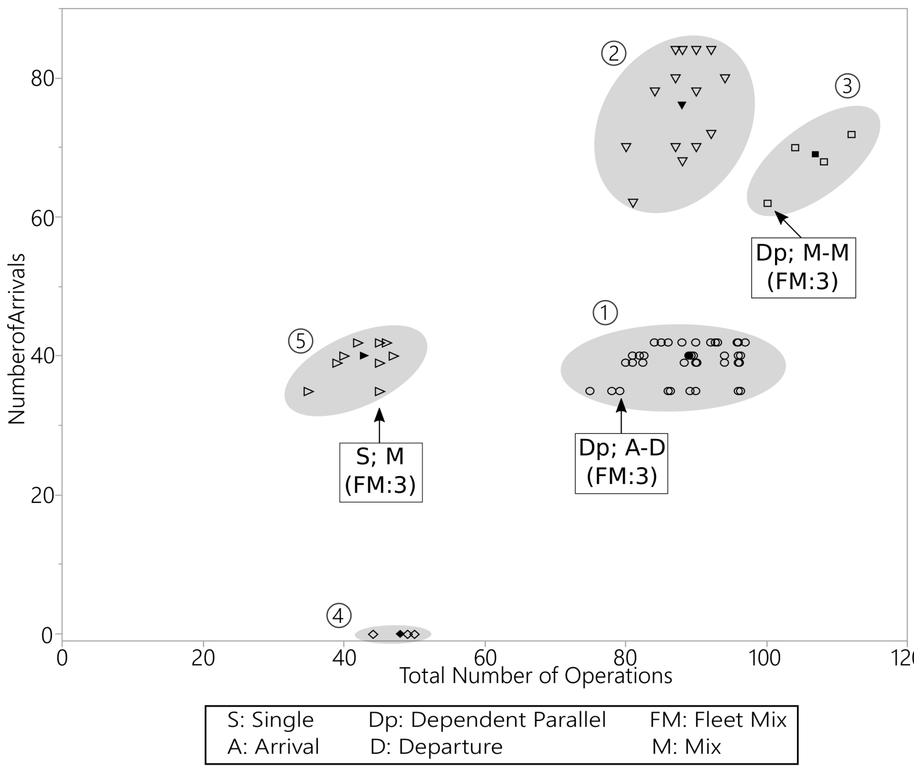


Fig. 10



80
60
40
20
0
NumberofArrivals
0
20
40
60
80
100
120
Total Number of Operations
①
②
③
④
⑤
Dp; M-M
(FM:3)
Dp; A-D
(FM:3)
S; M
(FM:3)
S: Single
Dp: Dependent Parallel
FM: Fleet Mix
A: Arrival
D: Departure
M: Mix

Fig. 11

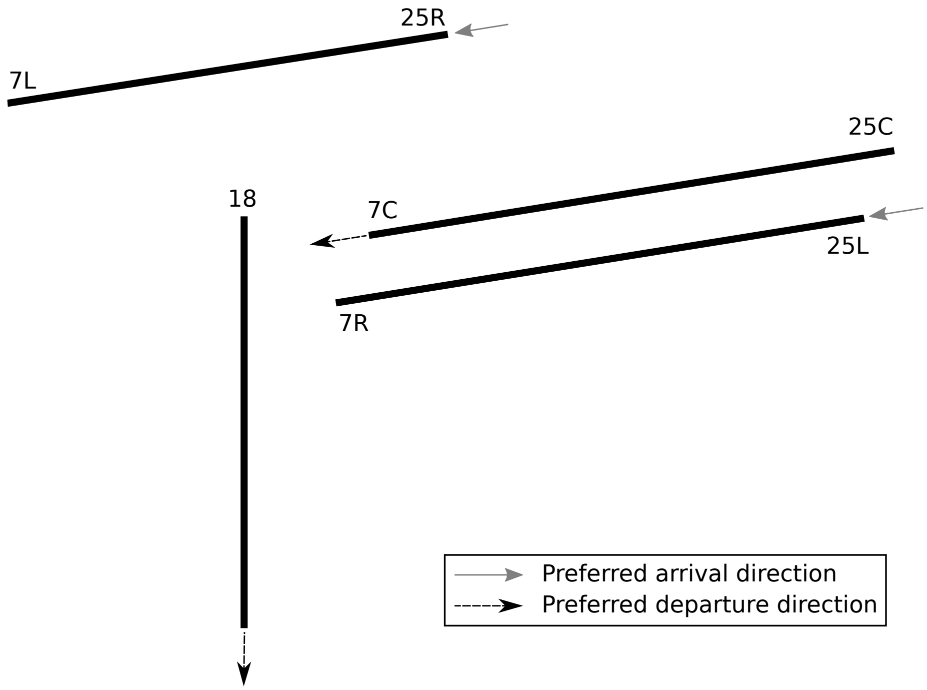

25R
7L
25C
18
7C
25L
7R
Preferred arrival direction
Preferred departure direction

Fig. 12

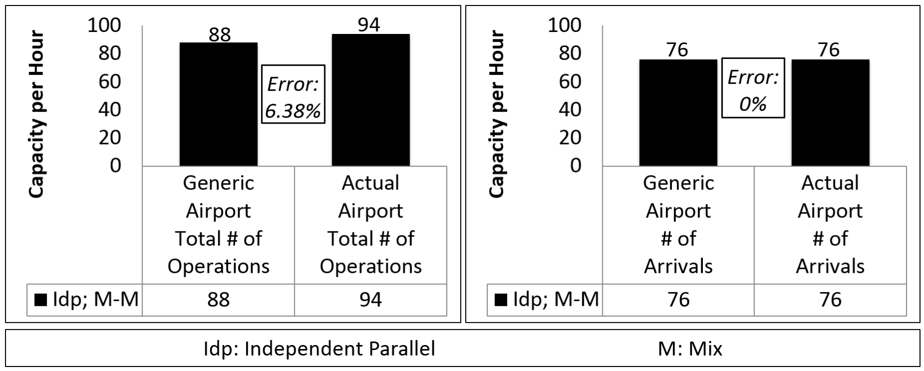

Capacity per Hour
100
80
60
40
20
0
88
94
Error: 6.38%
Generic Airport Total # of Operations
Actual Airport Total # of Operations
Idp; M-M
88
94
Capacity per Hour
100
80
60
40
20
0
76
76
Error: 0%
Generic Airport # of Arrivals
Actual Airport # of Arrivals
Idp; M-M
76
76
Idp: Independent Parallel
M: Mix

Fig. 13

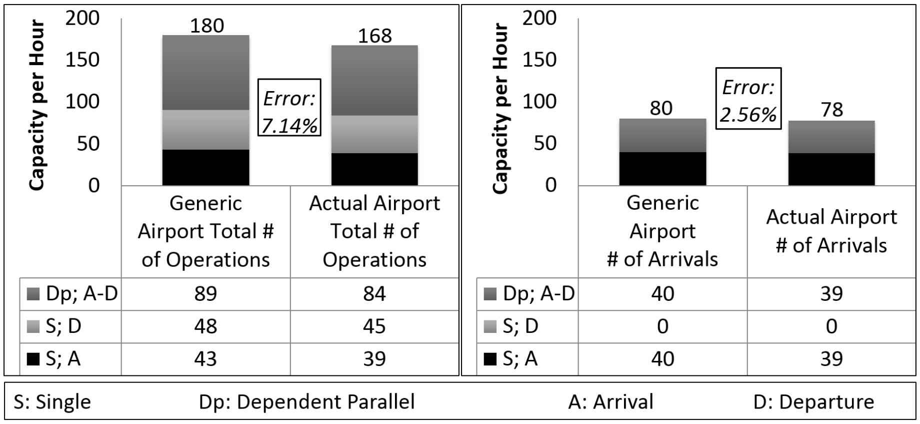

Capacity per Hour
200
150
100
50
0
180
168
Error: 7.14%
Generic Airport Total # of Operations
Actual Airport Total # of Operations
Dp; A-D 89 84
S; D 48 45
S; A 43 39
80
78
Error: 2.56%
Generic Airport # of Arrivals
Actual Airport # of Arrivals
Dp; A-D 40 39
S; D 0 0
S; A 40 39
S: Single
Dp: Dependent Parallel
A: Arrival
D: Departure

Fig. 14

Appendix

The Categorical Capacity Model look-up table for elemental runway configurations combined with fleet mix clusters are given in the following tables with representative capacity values for total number of operations and number of arrivals. Fleet mix clusters and corresponding distributions can be found in Table 4.

Runway Capacity Cluster 1			
Total # of Operations: 89		**# of Arrivals: 40**	
Fleet Mix Cluster	*Runway Style*	*Runway Orientation*	*Runway Operation*
1	Intersecting	Close, Diverging	Arrival - Departure
1	Intersecting	Close, Diverging	Mix - Departure
1	Intersecting	Far, Converging	Arrival - Departure
1	Intersecting	Far, Converging	Mix - Departure
1	Diverging	Open End	Arrival - Departure
1	Diverging	Open End	Mix - Departure
1	Converging	Closed End	Arrival - Departure
1	Parallel	Dependent	Arrival - Departure
1	Parallel	Independent	Arrival - Departure
1	Parallel	Dependent	Mix - Departure
1	Parallel	Independent	Mix - Departure
2	Intersecting	Close, Diverging	Arrival - Departure
2	Intersecting	Close, Diverging	Mix - Departure
2	Intersecting	Far, Converging	Arrival - Departure
2	Intersecting	Far, Converging	Mix - Departure
2	Diverging	Open End	Arrival - Departure
2	Diverging	Open End	Mix - Departure
2	Converging	Closed End	Arrival - Departure
2	Parallel	Dependent	Arrival - Departure
2	Parallel	Independent	Arrival - Departure
2	Parallel	Dependent	Mix - Departure
2	Parallel	Independent	Mix - Departure
3	Intersecting	Close, Diverging	Arrival - Departure
3	Intersecting	Close, Diverging	Mix - Departure
3	Intersecting	Far, Converging	Arrival - Departure
3	Intersecting	Far, Converging	Mix - Departure
3	Diverging	Open End	Arrival - Departure
3	Diverging	Open End	Mix - Departure
3	Converging	Closed End	Arrival - Departure
3	Parallel	Dependent	Arrival - Departure
3	Parallel	Independent	Arrival - Departure
3	Parallel	Dependent	Mix - Departure
3	Parallel	Independent	Mix - Departure
4	Intersecting	Close, Diverging	Arrival - Departure

Runway Capacity Cluster 1 *(continued)*			
Total # of Operations: 89		**# of Arrivals: 40**	
Fleet Mix Cluster	*Runway Style*	*Runway Orientation*	*Runway Operation*
4	Intersecting	Close, Diverging	Mix - Departure
4	Intersecting	Far, Converging	Arrival - Departure
4	Intersecting	Far, Converging	Mix - Departure
4	Diverging	Open End	Arrival - Departure
4	Diverging	Open End	Mix - Departure
4	Converging	Closed End	Arrival - Departure
4	Parallel	Dependent	Arrival - Departure
4	Parallel	Independent	Arrival - Departure
4	Parallel	Dependent	Mix - Departure
4	Parallel	Independent	Mix - Departure
5	Intersecting	Close, Diverging	Arrival - Departure
5	Intersecting	Close, Diverging	Mix - Departure
5	Intersecting	Far, Converging	Arrival - Departure
5	Intersecting	Far, Converging	Mix - Departure
5	Diverging	Open End	Arrival - Departure
5	Diverging	Open End	Mix - Departure
5	Converging	Closed End	Arrival - Departure
5	Parallel	Dependent	Arrival - Departure
5	Parallel	Independent	Arrival - Departure
5	Parallel	Dependent	Mix - Departure
5	Parallel	Independent	Mix - Departure

Runway Capacity Cluster 2			
Total # of Operations: 88		**# of Arrivals: 76**	
Fleet Mix Cluster	*Runway Style*	*Runway Orientation*	*Runway Operation*
1	Parallel	Dependent	Mix - Arrival
1	Parallel	Independent	Mix - Arrival
1	Parallel	Independent	Mix - Mix
2	Parallel	Dependent	Mix - Arrival
2	Parallel	Independent	Mix - Arrival
2	Parallel	Independent	Mix - Mix
3	Parallel	Dependent	Mix - Arrival
3	Parallel	Independent	Mix - Arrival
3	Parallel	Independent	Mix - Mix
4	Parallel	Dependent	Mix - Arrival
4	Parallel	Independent	Mix - Arrival
4	Parallel	Independent	Mix - Mix
5	Parallel	Dependent	Mix - Arrival
5	Parallel	Independent	Mix - Arrival
5	Parallel	Independent	Mix - Mix

Runway Capacity Cluster 3			
Total # of Operations: 107		**# of Arrivals: 69**	
Fleet Mix Cluster	*Runway Style*	*Runway Orientation*	*Runway Operation*
1	Parallel	Dependent	Mix - Mix
2	Parallel	Dependent	Mix - Mix
3	Parallel	Dependent	Mix - Mix
4	Parallel	Dependent	Mix - Mix
5	Parallel	Dependent	Mix - Mix

Runway Capacity Cluster 4			
Total # of Operations: 48		**# of Arrivals: 0**	
Fleet Mix Cluster	*Runway Style*	*Runway Orientation*	*Runway Operation*
1	Single	Independent	Departure
2	Single	Independent	Departure
3	Single	Independent	Departure
4	Single	Independent	Departure
5	Single	Independent	Departure

Runway Capacity Cluster 5			
Total # of Operations: 43		**# of Arrivals: 40**	
Fleet Mix Cluster	*Runway Style*	*Runway Orientation*	*Runway Operation*
1	Single	Independent	Arrival
1	Single	Independent	Mix
2	Single	Independent	Arrival
2	Single	Independent	Mix
3	Single	Independent	Arrival
3	Single	Independent	Mix
4	Single	Independent	Arrival
4	Single	Independent	Mix
5	Single	Independent	Arrival
5	Single	Independent	Mix